# NYU Politics Data Lab Workshop: Scraping Twitter and Web Data Using R

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## Scraping the web: what? why?

- Increasing amount of data is available on the web:
  - Election results, budget allocations, legislative speeches
  - Social media data, newspapers articles
  - Geographic information, weather forecasts, sports scores
- These data are provided in an unstructured format: you can always copy&paste, but it's time-consuming and prone to errors.
- Web scraping is the process of extracting this information automatically and transform it into a structured dataset.
- Two different scenarios:
  1. Web APIs (application programming interface): website offers a set of structured *http* requests that return JSON or XML files.
  2. Screen scraping: extract data from source code of website, with *html* parser (easy) or regular expression matching (less easy).
- Why `R`? It includes all tools necessary to do web scraping, familiarity, direct analysis of data... But python, perl, java are probably more efficient tools. Whatever works for you!

## The rules of the game

1. Respect the hosting site's wishes:
    - Check if an API exists first, or if data are available for download.
    - Some websites "disallow" scrapers on their `robots.txt` files.
2. Limit your bandwidth use:
    - Wait one second after each hit
    - Try to scrape websites during off-peak hours
    - Scrape only what you need, and just once
3. When using APIs, read terms and conditions.
    - The fact that you can access some data doesn't mean you should use it for your research.
    - Be aware of rate limits.
    - Ongoing debate on replication of social science research using this source of data.

## Outline

- Rest of the workshop: learning with four toy examples.
- Downloading data using Web APIs
  1. Finding influential users using Twitter's REST API
  2. Capturing and analyzing tweets in realtime using the Streaming API
- Screen scraping of HTML websites
  4. Extracting district-level electoral results in Georgia
  5. Constructing a dataset of bribes paid in India
- Code and data: http://www.pablobarbera.com/workshop.zip
- Fork my repo! http://github.com/pablobarbera/workshop

## Introduction to the Twitter API

Why Twitter?

- 140M active Twitter users. 16% online Americans use it.
- Meaningful public conversations; use for political purposes
- Cheap, fast, easy access, contextual information

There are two ways of getting Twitter data:

1. RESTful API:
    - Queries for specific information about users and tweet
    - Examples: user profile, list of followers and friends, tweets generated by a given user, users lists...
    - R library: twitteR
2. Streaming API:
    - Connect to the "stream" of tweets as they are being published
    - Examples: random sample of all tweets, tweets that mention a keyword, tweets from a set of users...
    - R library: streamR
3. More: dev.twitter.com/docs/api/1.1

## Authentication

- Most APIs require authentication to limit number of hits per user.
- Twitter (and many others) use an open standard called OAuth 1.0, which allows connections without sharing username and password.
- Currently all queries to Twitter's API require a valid OAuth "token".
- How to get yours:
  1. Create new application on dev.twitter.com
  2. Save consumer key and consumer secret
  3. Go to `01_getting_OAuth_token.R` and run the code.
  4. Save token for future sessions.

## 1. Finding influential users in a small network

- Twitter as a directed network, where “edges” are following relationships across users
- Common (strong) assumption: more followers implies more influence.
- Who is the most influential Twitter user at the NYU Politics Department?
- We will learn how to:
  1. Download user information
  2. Extract list of followers/friends
  3. Apply snowball sampling to construct dept. network
  4. Quick visualization of the network
- Code: `02_analysis_twitter_nyu.R`

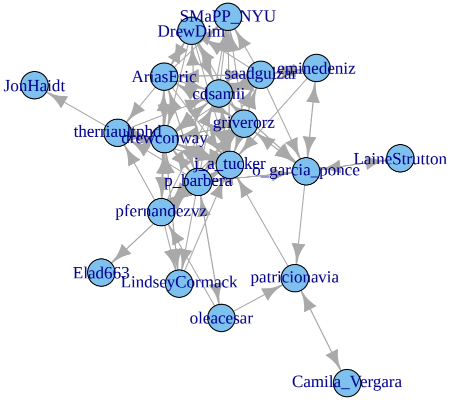
```
# getting data for seed user
seed <- getUser("drewconway")
seed.n <- seed$screenName
seed.n

## [1] "drewconway"

# saving list of Twitter users he follows
following <- seed$getFriends()
following.n <- as.character(lapply(following, function(x) x$getScreenName()))
head(following.n)

## [1] "MikeGruz"     "johnjhorton"  "anthlittle"   "theumpires"
## [5] "JennyVrentas" "dturkenk"

# creating list to be filled with friends for each NYU user
follow.list <- list()
follow.list[[seed.n]] <- following.n
```

```
# extracting description of users
descriptions <- as.character(lapply(following, function(x) x$getDescription()))
descriptions[1]
## [1] "Political science Ph.D student, lover of fine booze and shenanigans, courag
# function to subset only users from NYU-Politics
extract.nyu <- function(descriptions) {
    nyu <- grep("nyu|new york university", descriptions, ignore.case = T)
    poli <- grep("poli(tics|tical|sci)", descriptions, ignore.case = T)
    others <- grep("policy|wagner|cooperation", descriptions, ignore.case = T)
    nyu.poli <- intersect(nyu, poli)
    nyu.poli <- nyu.poli[nyu.poli %in% others == FALSE]
    return(nyu.poli)
}
# and now subsetting Twitter users from NYU-Politics
nyu <- extract.nyu(descriptions)
nyu.users <- c(seed$screenName, following.n[nyu], "cdsamii")
nyu.users
## [1] "drewconway"    "p_barbera"     "griverorz"     "j_a_tucker"
## [5] "pfernandezvz"  "LindseyCormack" "cdsamii"
```

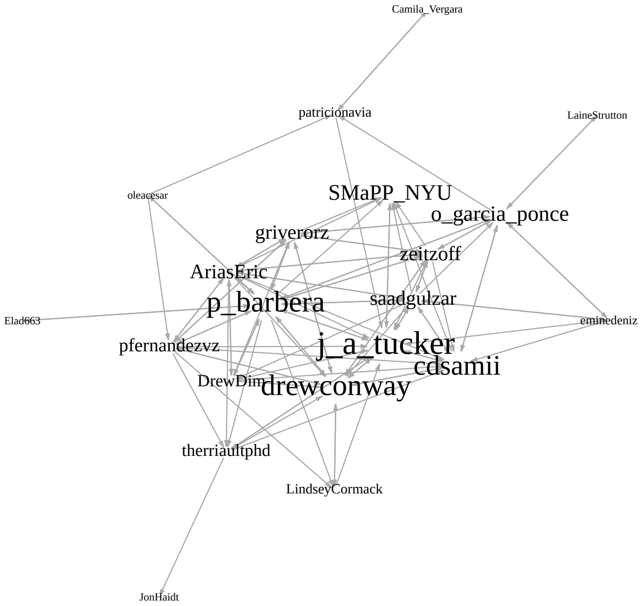
```r
# loop over NYU users following same steps
while (length(nyu.users) > length(follow.list)) {
    # pick first user not done
    user <- nyu.users[nyu.users %in% names(follow.list) == FALSE][1]
    user <- getUser(user)
    user.n <- user$screenName
    # download list of users he/she follows
    following <- user$getFriends()
    friends <- as.character(lapply(following, function(x) x$getScreenName()))
    follow.list[[user.n]] <- friends
    descriptions <- as.character(lapply(following, function(x) x$getDescription()))
    # subset and add users from NYU Politics
    nyu <- extract.nyu(descriptions)
    new.users <- lapply(following[nyu], function(x) x$getScreenName())
    new.users <- as.character(new.users)
    nyu.users <- unique(c(nyu.users, new.users))
    # if rate limit is hit, wait for a minute
    limit <- getCurRateLimitInfo()[44, 3]
    while (limit == "0") {
        Sys.sleep(60)
        limit <- getCurRateLimitInfo()[44, 3]
    }
}
```

```
nyu.users <- names(follow.list)

# for each user, find which NYU users follow
adjMatrix <- lapply(follow.list, function(x) (nyu.users %in% x) * 1)

# transform into an adjacency matrix
adjMatrix <- matrix(unlist(adjMatrix), nrow = length(nyu.users), byrow = TRUE,
    dimnames = list(nyu.users, nyu.users))
adjMatrix[1:5, 1:5]

##             drewconway cdsamii p_barbera griverorz j_a_tucker
## drewconway           0       1         1         1          1
## cdsamii              1       0         0         0          1
## p_barbera            1       0         0         1          1
## griverorz            1       0         1         0          0
## j_a_tucker           1       1         1         0          0
```

```
library(igraph)
network <- graph.adjacency(adjMatrix)
plot(network)
```



```
# computing indegree (followers in NYU dept)
degrees <- degree(network, mode="in")
degrees[1:5]

## drewconway    cdsamii  p_barbera  griverorz j_a_tucker
##         10          9         10          5         12

# weigh label size by indegree
V(network)$label.cex <- (degrees/max(degrees)*1.25)+0.5
## choose layout that maximizes distances
set.seed(1234)
l <- layout.fruchterman.reingold.grid(network, niter=1000)
# draw nice network plot
pdf("network_nyu.pdf", width=6, height=6)
plot(network, layout=l, edge.width=1, edge.arrow.size=.25,
          vertex.label.color="black", vertex.shape="none",
          margin=-.15)
dev.off()

## pdf
##   2
```


Camila_Vergara
patricionavia
LaineStrutton
oleacesar
SMaPP_NYU
o_garcia_ponce
griverorz
zeitzoff
AriasEric
p_barbera
saadgulzar
Elad663
eminedeniz
pfernandezvz
j_a_tucker
cdsamii
DrewDim
drewconway
therriaultphd
LindseyCormack
JonHaidt

## How to collect tweets

- For a quick analysis, you could use the SearchTwitter function in the twitteR package:

```
searchTwitter("#PoliSciNSF", n = 1)

## [[1]]
## [1] "Jen_at_APSA: Is the Republican attack on political science self-defeati
```

- Code: 03_tweets_search.R
- Limitations:
  - Not all tweets are indexed or made available via search.
  - Does not contain user metadata
  - Limited to a few thousand most recent tweets
  - Old tweets are not available.

## Streaming API

- Recommended method to collect tweets
- Firehose: real-time feed of all public tweets (400M tweets/day = 1 TB/day), but expensive.
- Spritzer: random 1% of all public tweets (4.5K tweets/minute = 8 GB/day), implemented in streamR as `sampleStream`
- Filter: public tweets filtered by keywords, geographic regions, or users, implemented as `filterStream`.
- Issues:
  - Filter streams have same rate limit as spritzer (1% of all tweets)
  - Stream connections tend to die spontaneously. Restart regularly.
  - Lots of invalid content in stream. If it can't be parsed, drop it.

## Anatomy of a tweet

```
{ "created_at":"Wed Nov 07 04:16:18 +0000 2012",
  "id":266031293945503744,
  "id_str":"266031293945503744",
  "text":"Four more years. http://t.co/bAJE6Vom",
  "source":"web",
  "user":
  { "id":813286,
    "id_str":"813286",
    "name":"Barack Obama",
    "screen_name":"BarackObama",
    "location":"Washington, DC",
    "url":"http://www.barackobama.com",
    "description":"This account is run by #Obama2012 campaign staff.
      Tweets from the President are signed -bo.",
    "protected":false,
    "followers_count":23487605,
    "friends_count":670339,
    "listed_count":182313,
    "created_at":"Mon Mar 05 22:08:25 +0000 2007",
    "utc_offset":-18000,
    "time_zone":"Eastern Time (US & Canada)",
    "geo_enabled":false,
    "verified":true,
    "statuses_count":7972,
    "lang":"en" },
  "geo":null,
  "coordinates":null,
  "place":null,
  "retweet_count":816600 }
```

Tweets are encoded in JSON format.

3 types of information:

1. Tweet information
2. User information
3. Geographic information

## 2. Capturing and analyzing tweets using the Streaming API

- We will learn how to:
  1. Capture tweets that contain a given keyword
  2. Basic sentiment analysis
  3. Capture geo-tagged tweets from a given location
  4. Map tweets by location
- Code: `04_tweets_by_keyword.R` and `05_tweets_by_location.R`.
- Note that you will need a more robust workflow to do this at a larger scale. I personally use:
  - Amazon EC2 Ubuntu micro instance (free tier)
  - Cron jobs to restart R scripts every hour.
  - Save tweets in .json files or in mySQL tables.

## Capturing tweets by keyword

```
# loading library and OAuth token
library(streamR, quietly = TRUE)
```

```
load("my_oauth")
# capturing 3 minutes of tweets mentioning obama or biden
filterStream(file.name = "tweets_keyword.json", track = c("obama", "biden"),
    timeout = 180, oauth = my_oauth)
```

```
# parsing tweets into dataframe
tweets <- parseTweets("tweets_keyword.json", verbose = TRUE)

## 317 tweets have been parsed.
```

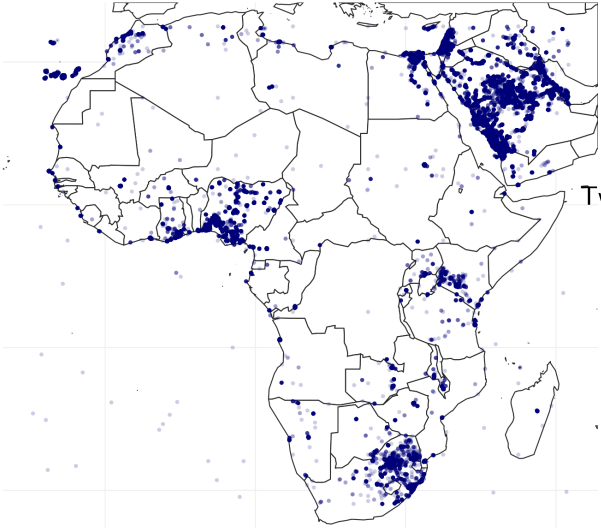
```
# preparing words for analysis
clean.tweets <- function(text) {
    # loading required packages
    lapply(c("tm", "Rstem", "stringr"), require, c = T, q = T)
    words <- removePunctuation(text)
    words <- wordStem(words)
    # spliting in words
    words <- str_split(text, " ")
    return(words)
}

# classify an individual tweet
classify <- function(words, pos.words, neg.words) {
    # count number of positive and negative word matches
    pos.matches <- sum(words %in% pos.words)
    neg.matches <- sum(words %in% neg.words)
    return(pos.matches - neg.matches)
}
```

```
# function that applies sentiment classifier
classifier <- function(tweets, pos.words, neg.words, keyword) {
    # subsetting tweets that contain the keyword
    relevant <- grep(keyword, tweets$text, ignore.case = TRUE)
    # preparing tweets for analysis
    words <- clean.tweets(tweets$text[relevant])
    # classifier
    scores <- unlist(lapply(words, classify, pos.words, neg.words))
    n <- length(scores)
    positive <- as.integer(length(which(scores > 0))/n * 100)
    negative <- as.integer(length(which(scores < 0))/n * 100)
    neutral <- 100 - positive - negative
    cat(n, "tweets about", keyword, ":", positive, "% positive,", negative,
        "% negative,", neutral, "% neutral")
}
```

```r
# loading lexicon of positive and negative words
lexicon <- read.csv("lexicon.csv", stringsAsFactors = F)
pos.words <- lexicon$word[lexicon$polarity == "positive"]
neg.words <- lexicon$word[lexicon$polarity == "negative"]

# applying classifier function
classifier(tweets, pos.words, neg.words, keyword = "obama")

## 294 tweets about obama : 13 % positive, 16 % negative, 71 % neutral

classifier(tweets, pos.words, neg.words, keyword = "biden")

## 16 tweets about biden : 31 % positive, 0 % negative, 69 % neutral
```

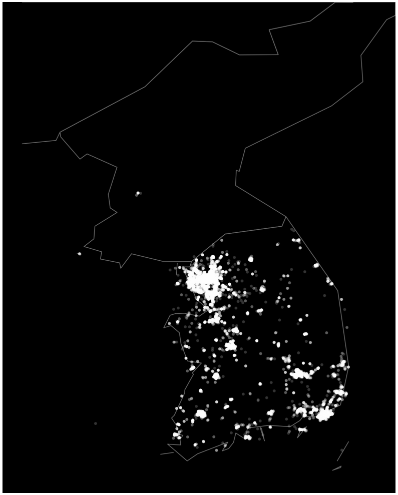
## Capturing tweets by location

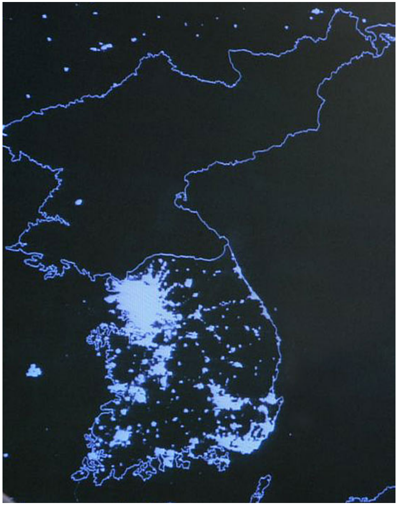
```r
# loading library and OAuth token
library(streamR)
load("my_oauth")

# capturing 2 minutes of tweets sent from Africa
filterStream(file.name = "tweets_africa.json", locations = c(-20, -37, 52, 35),
    timeout = 120, oauth = my_oauth)
# parsing tweets into dataframe
tweets.df <- parseTweets("tweets_africa.json", verbose = TRUE)
```



Tweets from Africa:

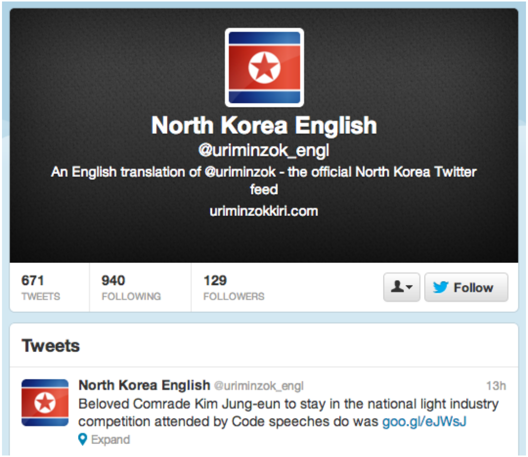
- 358,374 tweets collected for 24 hours on March 17th.





Tweets from Korea: 41,194 tweets collected on March 18th (left)
Korean peninsula at night, 2003 (right). Source: NASA.

## Who is tweeting from North Korea?



North Korea English
@uriminzok_engl
An English translation of @uriminzok - the official North Korea Twitter feed
uriminzokkiri.com

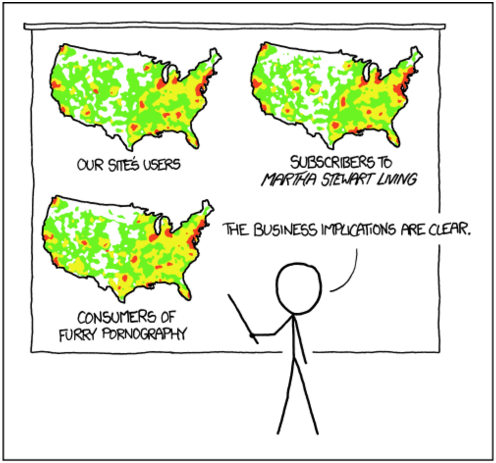
671 TWEETS | 940 FOLLOWING | 129 FOLLOWERS

Tweets

North Korea English @uriminzok_engl 13h
Beloved Comrade Kim Jung-eun to stay in the national light industry competition attended by Code speeches do was goo.gl/eJWsJ

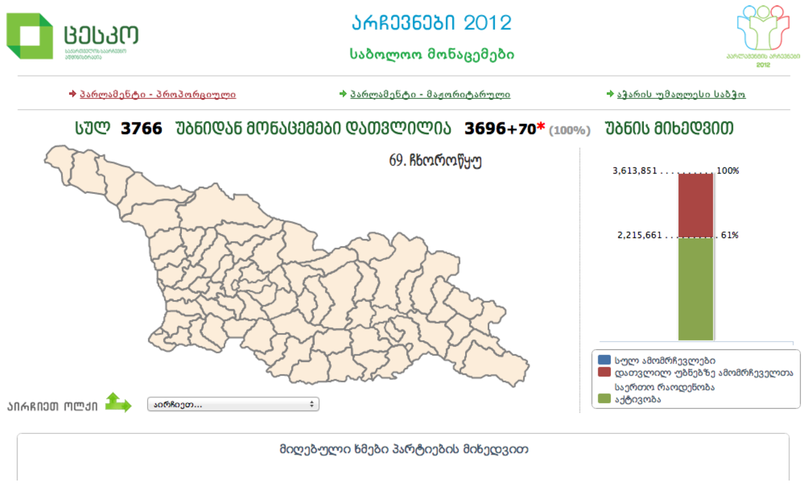
Twitter user: @uriminzok_engl

## But remember...


OUR SITE'S USERS
SUBSCRIBERS TO MARTHA STEWART LIVING
CONSUMERS OF FURRY PORNOGRAPHY
THE BUSINESS IMPLICATIONS ARE CLEAR.

PET PEEVE #208:
GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

## Scraping electoral results in Georgia


ცესკო
არჩევნები 2012
საბოლოო მონაცემები
პარლამენტი - პროპორციული
პარლამენტი - მაჟორიტარული
აჭარის უმაღლესი საბჭო
სულ 3766 უბნიდან მონაცემები დათვლილია 3696+70* (100%) უბნის მიხედვით
69. ჩხოროწყუ
3,613,851
100%
2,215,661
61%
🟦 სულ ამომრჩევლები
🟥 დათვლილ უბნებზე ამომრჩეველთა საერთო რაოდენობა
🟩 აქტივობა
აირჩიეთ ოლქი
აირჩიეთ...
მიღებული ხმები პარტიების მიხედვით

URL: Central Electoral Comission of Georgia

## 3.Scraping electoral results in Georgia

- District-level results are not available for direct download
- However, information is structured in a series of html tables
- Even original document with electoral returns can be downloaded!
- We will learn how to:
  1. Parse HTML tables
  2. Use regular expressions to “clean” data
  3. Program function that parses list of URLs
  4. Quick visualization of results
- Code: `06_scraping_election_georgia.R`

```
library(XML)
url <- "http://results.cec.gov.ge/index.html"
table <- readHTMLTable(url, stringsAsFactors = F)
# how to know which table to extract?  run 'str(table)' and look for table
# of interest.  Alternatively, search html code for table ID
table <- table$table36
table[1:6, 2:6]

##            V2         V3            V4         V5          V6
## 1           1          4             5          9          10
## 2 222(0.56%)  51(0.13%) 13229(33.44%) 16(0.04%)  413(1.04%)
## 3 380(0.54%)  92(0.13%) 16728(23.62%) 44(0.06%)  939(1.33%)
## 4  358(0.4%) 123(0.14%) 22539(25.06%) 56(0.06%) 1047(1.16%)
## 5  82(0.31%)   27(0.1%)  9991(37.67%) 64(0.24%)   344(1.3%)
## 6 164(0.26%)  56(0.09%) 19778(31.06%) 92(0.14%) 1052(1.65%)
```

```
# deleting percentages (anything inside parentheses)
library(plyr)
table <- ddply(table, 2:18, function(x) gsub("\\(.*\\)", "", x))
# changing variable names
names(table) <- c("district", paste0("party_", table[1, 2:18]))
# deleting unnecessary row/column (party names and empty column)
table <- table[-1, -18]
# fixing district names
table$district <- as.numeric(gsub("(.*)\\..*", repl = "\\1", table$district))
# fixing variable types
table[, 2:17] <- apply(table[, 2:17], 2, as.numeric)
table[1:5, 1:5]

##   district party_1 party_4 party_5 party_9
## 2        1     222      51   13229      16
## 3        2     380      92   16728      44
## 4        3     358     123   22539      56
## 5        4      82      27    9991      64
## 6        5     164      56   19778      92
```

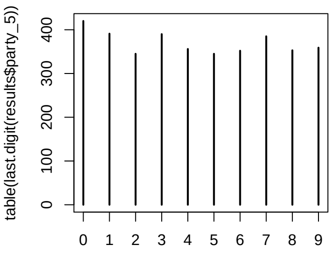
## Scraping district-level electoral results

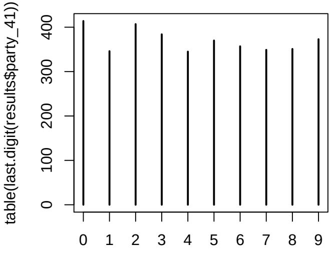
```
# list of district numbers
districts <- table$district
# replicate same steps as above for each district
extract.results <- function(district) {
    # read and parse html table
    url <- paste0("http://results.cec.gov.ge/olq_", district, ".html")
    results <- readHTMLTable(url, stringsAsFactors = F)
    results <- results$table36
    # variable names = party numbers
    names(results) <- c("section", paste0("party_", results[1, 2:length(results
    # deleting first row and last column
    results <- results[-1, -length(results)]
    results$district <- district
    return(results)
}
```

```
# empty list to populate with district-level data
results <- list()
# loop over districts
for (district in districts) {
    results[[district]] <- extract.results(district)
}
# convert list to data.frame
results <- do.call(rbind, results)
```

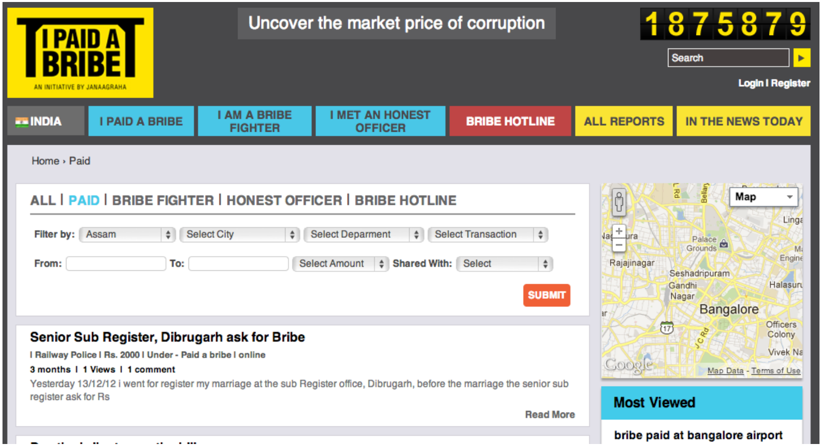
```
results[1:5, c(1:5, length(results))]

##   section party_1 party_4 party_5 party_9 district
## 2       1       8       2     262       0        1
## 3       2       0       0     239       1        1
## 4       3       4       0     287       2        1
## 5       4       5       4     197       0        1
## 6       5       6       1     284       0        1
```

```
# function to extract last digit
last.digit <- function(votes) {
    last.pos <- nchar(votes)
    as.numeric(substring(votes, last.pos, last.pos))
}
# histogram of last digit for two main parties
plot(table(last.digit(results$party_5)))
plot(table(last.digit(results$party_41)))
```





## Scraping bribes data from India



Senior Sub Register, Dibrugarh ask for Bribe

I Railway Police I Rs. 2000 I Under - Paid a bribe I online

3 months I 1 Views I 1 comment

Yesterday 13/12/12 i went for register my marriage at the sub Register office, Dibrugarh, before the marriage the senior sub register ask for Rs

Read More

bribe paid at bangalore airport

URL: www.ipaidabribe.com

## 4. Constructing a dataset of bribes paid in India

- Crowdsourcing to combate corruption: `ipaidabribe.com`
- Data on 18,000 bribes paid in Indian, self-reported
- Information about how much, where, and why.
- We will learn how to:
    - Parse semi-structured HTML code
    - Find “node” of interest and extract it
    - Use regular expressions to clean data
    - Prepare a short script to extract data recursively
- Code: `07_scraping_india_bribes.R`

## Introduction to regular expressions

- Regular expressions (regex) are patterns used to "match" text strings.
- Used in combination with `grep` (find) and `gsub` (find and replace all)
- Most common expression patterns:
  - `.` matches any character, `^` and `$` match beginning and end of line.
  - Any character followed by `{3}`, `*`, `+` is matched exactly 3 times, 0 or more times, 1 or more times.
  - `[0-9]`, `[a-ZA-Z]`, `[:alnum:]` matches any digit, any letter, or any digit and letter.
  - To extract pattern (not just replace), use parentheses and option `repl="\\1"`.
  - In order to match special characters (`. \ ( )` etc), they need to preceded by a backslash.
  - Type `?regex` for more details.
- Perl regex can also be used in `R` (option `perl=TRUE`)

```r
# Starting with the first page
url <- "http://www.ipaidabribe.com/reports/paid"
# read html code from website
url.data <- readLines(url)

# parse HTML tree into an R object
library(XML)
doc <- htmlTreeParse(url.data, useInternalNodes = TRUE)

# extract what we need: descriptions and basic info for each bribe
titles <- xpathSApply(doc, "//div[@class='teaser-title']", xmlValue)
attributes <- xpathSApply(doc, "//div[@class='teaser-attributes']", xmlValue)
```

```r
# note that we only need the first 10
titles <- titles[1:10]
attributes <- attributes[1:10]

## all those '\t' and '\n' are just white spaces that we can trim
library(stringr)
titles <- str_trim(titles)

# the same for the bribe characteristics
cities <- gsub(".*[\t]{4}(.*)[\t]{5}.*", attributes, replacement = "\\1")
depts <- gsub(".*\n\t\t    (.*)\t\t.*", attributes, replacement = "\\1")
amounts <- gsub(".*Rs. ([0-9]*).*", attributes, replacement = "\\1")

# we can put it together in a matrix
page.data <- cbind(titles, cities, depts, amounts)
```

```r
# let's wrap it in a single function
extract.bribes <- function(url) {
    require(stringr)
    cat("url:", url)
    url.data <- readLines(url)
    doc <- htmlTreeParse(url.data, useInternalNodes = TRUE)
    titles <- xpathSApply(doc, "//div[@class='teaser-title']", xmlValue)[1:10]
    attributes <- xpathSApply(doc, "//div[@class='teaser-attributes']", xmlValu
    titles <- str_trim(titles)
    cities <- gsub(".*[\t]{4}(.*)[\t]{5}.*", attributes, replacement = "\\1")
    depts <- gsub(".*\n\t\t    (.*)\t\t.*", attributes, replacement = "\\1")
    amounts <- gsub(".*Rs. ([0-9]*).*", attributes, replacement = "\\1")
    return(cbind(titles, cities, depts, amounts))
}
```

```r
## all urls
urls <- paste0("http://www.ipaidabribe.com/reports/paid?page=", 0:50)

## empty array
data <- list()

## looping over urls...
for (i in seq_along(urls)) {
    # extracting information
    data[[i]] <- extract.bribes(urls[i])
    # waiting one second between hits
    Sys.sleep(1)
    cat(" done!\n")
}

## transforming it into a data.frame
data <- data.frame(do.call(rbind, data), stringsAsFactors = F)
```

```
# quick summary statistics
head(sort(table(data$depts), dec = T))

##
##                  Railway Police                              Police
##                             406                                  36
##                        Airports          Stamps and Registration
##                              13                                  11
##                        Passport Customs, Excise and Service Tax
##                               9                                   7

head(sort(table(data$cities), dec = T))

##
##           Bangalore      Mumbai New Delhi       Pune    Gurgaon
##       157       151          47        23         23         12

summary(as.numeric(data$amounts))

##     Min. 1st Qu.  Median     Mean 3rd Qu.    Max.    NA's
##        0     200     800    66600    4000 5000000       1
```

## References

- Jackman, Simon. 2006. "Data from the Web into R". *The Political Methodologist*, 14(2).
- Hanretty, Chris. *Scraping the Web for Arts and Humanities*. LINK
- Leipzig, Jeremy and Xiao-Yi Li. *Data Mashups in R*. O'Reilly
- Russell, Matthew. *Mining the Social Web*. O'Reilly.
- R libraries: scrapeR, XML, twitteR (check vignettes for examples)
- Python libraries: BeautifulSoup, tweepy
- Alex Hanna's *Tworkshops* LINK